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Analysis and Comparison of Sleeping Posture Classification Methods using Pressure Sensitive Bed System

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Abstract— **Pressure ulcers are common problems for bedridden patients. Caregivers need to reposition the sleeping posture of a patient every two hours in order to reduce the risk of getting ulcers. This study presents the use of Kurtosis and skewness estimation, principal component analysis (PCA) and support vector machines (SVMs) for sleeping posture classification using cost-effective pressure sensitive mattress that can help caregivers to make correct sleeping posture changes for the prevention of pressure ulcers.**

Keywords: sleeping posture, pressure sensor, Bayesian classification

I. INTRODUCTION

Pressure ulcer is a common problem for bedridden patients. It is caused by prolonged pressure to localized area of tissue resulted in occlusion of blood flow to the network of vascular and lymph vessels supplying oxygen and nutrients to the tissues [1]. The major factors are: the intensity of pressure, the duration of pressure, and the ability of tissue to tolerate pressure, complicated by the interplay of extrinsic and intrinsic variables that affect the tolerance of tissue [2,3,4].

Pressure ulcer is a major and costly issue in care institutions [5]. Caregivers need to change the sleeping posture of bedridden patients regularly in order to reduce the risk of developing pressure ulcers. If caregivers know the tissue tolerance ability of the patient and the sleeping postures of the patient during the past hours, caregivers can make the best sleeping posture adjustment for each patient to prevent the development of pressure ulcers.

Pressure sensing techniques have been used to measure interface pressure and monitor postures and movements of sleeping subjects [6-9]. Using pressure sensor pad, Harada et al. [7] have proposed a pressure distribution image-based human motion tracking system. A human's gross and slight movement estimation, and a distinction between sitting and lying status based on stick model have also been introduced by Harada et al. [8]. Considering the cost issue, Lowne et al. [9] have investigated the number of grid format pressure sensors. We are developing a sensor-based mattress system that can continuously collect extrinsic and intrinsic values of pressure ulcer factors of each patient, and provide caregivers with information to make intelligent decisions.

In this paper, we describe the design of force sensing resistor (FSR) based sensor mattress and the algorithms to determine sleeping postures, and discuss design considerations for a cost-effective sensor-based mattress system. Two different sensor layouts of FSR-based sensor pads were used in our experiments. We used a 16-sensor pad to evaluate the cost-effectiveness of a low-cost FSR-based sensor pad for sleeping posture detection. A 56-sensor pad was used to evaluate the effectiveness of posture detection using different combination of algorithms. Bayesian classification techniques: Kurtosis and skewness estimation, principal component analysis, descriptive statistics and support vector machines were utilized in our experiments to classify the sleeping postures.

The reminder of the paper is structured as follows. Section 2 describes the system architecture of the pressure sensitive bed system, the algorithms and data fusion methodologies applied in posture classification. The experimental results are discussed in Section 3. In Section 4, we discuss design considerations and future works. Finally, conclusion is given in Section 5.

II. SYSTEM OVERVIEW

The objective of this study is to develop an automated pressure sensing bed system which can provide helpful prompts to the caregivers when the subjects are at high potential bedsore risk. We develop both hardware and software systems in order to provide assistance to healthcare professionals and patients through ICT-enabled healthcare solution. Different sensor configurations of pressure sensing beds with the same type of pressure sensor can be seen in Figure 1. Two types of FSR from Interlink Electronics [10] were used: part no. 402 (0.5'' circle) and part no. 408 (24'' trimmable strip).

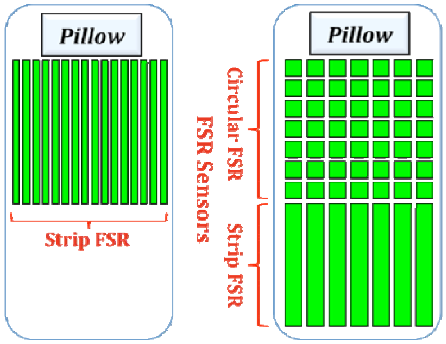

Figure 1: Sensing Bed Configuration with 16-sensor and 56-sensor Pads

The pressure sensing bed consists of FSR sensor matrix where pressure intensity readings are collected by embedded sensing platform. Then, acquired pressure data are sent to the data acquisition unit either though a CAN-based wired sensor network, or a Zigbee-based wireless sensor network platform [11]. Figure 2 illustrates the differences between wired and wireless pressure sensing bed system.

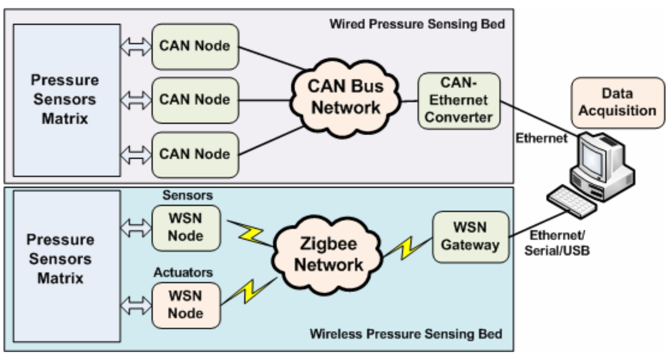

Figure 2 Pressure Sensing System using Wired and Wireless Platform

The diagram below illustrates how innovative healthcare applications can be designed and built with tiered software architecture approach. Sensing tier consists of the pressure sensing bed and associated data acquisition platform mentioned above. Data tier is concerned about the dissemination and storage of acquired pressure data in a scalable manner. The intelligence tier is composed of intelligence unit and application container to perform various levels of sensor processing and management in distributed ways. The client tier can observe the live pressure readings, subject states and clinical operations through provided visualization and user interfaces.

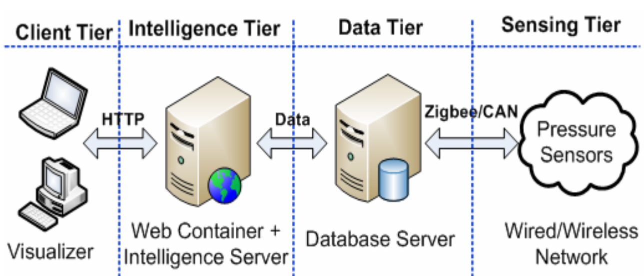

Figure 3: Tiered System Architecture

We design two-stage pressure data processing architecture including low-level sensor data processing and high-level activity recognition as illustrated in Figure 4. Low-level processing deals with direct pressure readings to identify the subject's states: on bed or not, sleeping posture, movements, etc. High-level recognition exploits pressure features and subject's states to recognize the bedsore risks and predict the bedsore states of the subject. Details of Bayesian inference, pressure features extraction with PCA [12] and descriptive statistics [13] and SVM [14] classification approaches for posture classification are presented in the following sections.

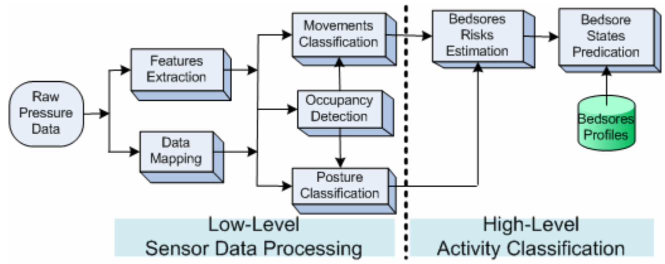

Figure 4. Software Modules and Framework for Bedsore Prevention

A. *Kurtosis and Skewness Estimation Approach*

Let $\omega=$ {supine, left lying, right lying} denote the class of sleeping posture, and $X=\{X_1, X_2, \cdots, X_N\}$ denote the set of normalized pressure values. N is the number of pressure sensors. The prior probabilities of sleeping postures $P(\omega)$ are assumed to be uniformly distributed. Gaussian distribution is adopted to model the bed postures on feature space. Based on posterior probability $P(\omega|X)$ and Bayesian theory, the bed posture is detected as:

$$\begin{aligned}\hat{\omega} &= \arg\max_{\omega} P(\omega \mid X) = \arg\max_{\omega} \frac{P(X \mid \omega) P(\omega)}{P(X)} \\ &= \arg\max_{\omega} P(X \mid \omega) = \arg\max_{\omega} N\left([k,s]'; \mathbf{\mu}_\omega, \mathbf{\Sigma}_\omega\right)\end{aligned} \tag{1}$$

where $\hat{\omega}$ denotes the detected sleeping posture. $[k,s]'$ is the feature vector estimated from the normalized pressure distribution X. Kurtossi k and Skewness s are estimated to represent the shape of the pressure distribution. $\mathbf{\mu}_\omega$ and $\mathbf{\Sigma}_\omega$ represent the mean vector and covariance matrix for class ω on the feature space.

Kurtosis and Skewness are calculated from the regenerated samples by regarding the pressure distribution X as a probability distribution. For example, let the total number of regenerated samples be 100 and the normalized pressure value for sensor 7 and sensor 8 be 0.15 and 0.20, the regenerated samples will consist of 15 samples with value 7, and 20 samples with value 8. The Kurtosis k is calculated as:

$$k = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_i \left(\frac{x_i - \bar{x}}{Std} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{2}$$

where n is the number of regenerated samples. x_i represents the regenerated sample. $\bar{x}$ and Std denote the sample mean and standard deviation of the regenerated samples. The Skewness s is estimated as:

$$s = \frac{n}{(n-1)(n-2)} \sum_i \left(\frac{x_i - \bar{x}}{Std} \right)^3 \tag{3}$$

B. PCA, Descriptive Statistics and SVM Classification Approach

PCA first transforms complex data set revealing hidden and simplified underlying structure that cannot be observed directly. So the salient spatial features for particular posture can be identified by finding orthogonal linear combinations of principal components. The salient features related to particular posture can be extracted by selecting the dominant principal components from eigenvectors of covariance matrix according to their ranks from ascending orders of eigenvalues.

Let $\mathbf{X} = \left\{ X_{n,m}; 1 \le n \le N, 1 \le m \le M \right\}$ denote the set of M data samples, each contains N normalized pressure values. The values of M and N are 80 and 56 respectively. Then, eigen decomposition is performed through computing covariance of mean-centralized pressure data sets $\mathbf{\Phi}_{bed}$ composing of $\phi_{n,m} = X_{n,m} - \bar{X}_n$. $\bar{X}_n$ is the mean value along the n^{th} row of $\mathbf{X}$. The covariance matrix is calculated as:

$$\mathbf{C}_{bed} = \frac{\mathbf{\Phi}_{bed} \mathbf{\Phi}'_{bed}}{M} \tag{4}$$

Finally, eigenvalues, μ_i and eigenvectors, $\mathbf{v}_i$ of covariance matrix $\mathbf{C}_{bed}$ can be directly computed as follows.

$$\mathbf{C}_{bed} \mathbf{v}_i = \mu_i \mathbf{v}_i \tag{5}$$

Similar to PCA, descriptive statistics such as mean, variance, standard deviation, root-mean squared features, etc. generally provide basic features of any data through simple summaries based on data dispersion and central tendency from pressure distributions. The feature vectors extracted from a set of pressure readings F_{stat} (X) over a specific area can be expressed as.

$$F_{stat}(X) = [F_{mean}(X), F_{rms}(X), F_{varience}(X), F_{stddev}(X)]^T \tag{6}$$

SVM is basically a non-parametric supervised binary classification technique based on statistical learning theory. It projects original raw pressure data or extracted features with PCA and descriptive statistics into higher dimensional space, specified by a kernel function, and, computes a maximum-margin hyper-plane decision surface that linearly separates the two or more classes. It can achieve best posture classification accuracy from pressure data and features through respective optimal hyperplanes. Three different classifiers are trained and constructed according to classifier inputs: raw pressure intensity data, Eigen vectors and descriptive statistical features. SVM classification can be presented as the following duality function.

$$f(x) = \sum_i \alpha_i K(x_i, x) + b \tag{7}$$

Its goal is to optimize the margin, ω constructing a classifier model with canonical separating hyper-planes through the scaled data sets, $\Theta(x_i)$

$$\omega = \sum_{i=1}^{m} \alpha_i \Theta(x_i) \tag{8}$$

The posture models were created and applied through training, cross-validation and testing phases using specific kernel and classifier parameters. By applying constructed classifier models, the sleeping posture class is predicted from unknown data sets in which only attributes are provided.

III. Experimental Results

In order to test and evaluate the different posture classification approaches, we collected a set of pressure readings from two different pressure sensor configurations (Figure 1) with specified sets of sleeping postures [15] as shown in Figure 5. Eight subjects participated in the experiment on data collection process. Each posture was repeated 3 times, each with a time period of 5 minutes. The pressure values were samples at 1 Hz for all sensors. The collected data were divided into training set (3 subjects) and test set (the other 5 subjects). Different posture classification methods are applied to the data sets of different pressure sensor configurations to identify the same posture classes.

Figure 5: Different Sleeping Postures to be classified

Table 1 provides posture classification results of Bayesian inference with Kurtosis and Skewness parameters using data collected from the 16-sensor configuration. As shown in this table, when the subjects lying in parallel to the bed center line, the Bayesian method could clearly classify the three main postures used in care institution: supine, left lying (left yearner/foetus/log) and right lying (right yearner/foetus/log). However, this method suffered from the lying angle effects, the average classification accuracy is 81.43%.

TABLE 1. DIFFERENT POSTURE CLASSIFICATION ACCURACIES (%) USING SKEWNESS AND KURTOSIS ESTIMATION

Posture / Lying angle	Left (Y/F/L)	Right (Y/F/L)	S
Parallel to the bed center line	100	100	100
30° clockwise or counterclockwise	93.5	86.2	64.6

Similarly, Table 2 provides the accuracies of SVM-based posture classification methods using a.) principal components from PCA, b.) raw pressure intensities of data, and c.) features from descriptive statistics, respectively.

TABLE 2. DIFFERENT POSTURE CLASSIFICATION ACCURACIES (%) USING PCA, DESCRIPTIVE STATISTICS AND SVM METHODS

Method	**R.Y**	**L.Y**	**L.F**	**R.F**	**L**	**S**
a.) PCA + SVM	58	53	64	68	70	75
b.) Raw Data + SVM	92	88	81	72	78	90
c.) Descriptive Statistics + SVM	95	74	73	78	75	71

IV. DISCUSSION AND FUTURE WORKS

The size and shape of FSR sensors and the density and placement of FSR sensor layouts can determine the effectiveness of sensor pad functions. The layouts of FSR sensors should match the mobility of the users and the event to be detected. In our experiments, we wanted to test the effectiveness of the simple 16-sensor layout in detecting patients sleeping on their back, right shoulder or left shoulder based on pressure data collected from the upper body of immobile or inactive patients. For patients with higher mobility, we used the 56-sensor layout to test its effectiveness in detecting lower body postures in addition to upper body postures.

Our results show that the 16-sensor configuration in Figure 1 can detect the three sleeping postures with high accuracy for patients with low mobility. Its accuracy starts to drop when patients move and sleep with different angles. We adopted SVM to classify the highly varying sleeping postures for the patients who are able to change their own postures. Compared to the Bayesian classification based on Kurtosis and Skewness features, SVM is more complicated with the ability to deal with the non-linear separable classification problems.

In many care institutions, caregivers use pillows to relieve pressures and avoid ulcer developments [16]. It interferes with posture recognition in two parts: feature estimation and posture model definition/estimation. In cases, for the patient who are immobile, an air mattress is usually used to automatically and regularly release the pressure part-by-part of the body. It results in adding noise into the process of pressure sensing. We are investigating high-level decision fusion and multi-modal sensor fusion to deal with real scenarios in care institutions.

V. CONCLUSION

Sleeping posture information is critical for caregivers to prevent the development of pressure ulcers, especially for immobile patients. We have designed a two-level data fusion architecture of a pressure sensitive bed system, and implemented the hardware and the software to evaluate our pressure sensor layouts and posture classification algorithms. Based on our initial results, we plan to add different sensors and apply multi-modal fusion techniques to monitor different events, reduce noise and improve event classification accuracy, and provide continuous sleeping activity information.

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